Mesoscale cloud state estimation from visible and infrared radiances

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1. Introduction

Current weather now-casting and forecasting require improving observational estimates of 3D distribution of cloud properties on mesoscales (Wu et al, 2000; Bayler et al, 2000; Wetzel et al., 2000; Chevallier and Kelly, 200). In situ, direct observations of the cloud 3D state are difficult to perform and in practice are limited to results of occasional field experiments. Systematic analysis of the cloud properties therefore require utilization of remote sensing measurements.

Previous studies on mesoscale cloud estimation from remote sensing have focused on radar measurements (Sun and Crook , 1998; Wu et al., 2000; Benedetti et al., 2003). In this study we explore the utilization of visible (VIS) and infrared (IR) satellite radiance measurements. These measurements have appealing properties of large spatial coverage, relatively high horizontal resolution and strong sensitivity to clouds (Chevallier and Kelly, 2002; Rossow and Garder, 1993). Our hypothesis is that the cloud state estimation from VIS and IR radiance observations is resolvable in the same manner as other atmospheric state estimation by way of optimal assimilation of observations into a state evolution model (Cohn, 1997). It is crucial for this approach that the cloud state is modeled as spatially distributed hydrometeors characterized with microphysical properties. Similar to previous cloud state estimation studies we use a variational data assimilation method with time dimension included. The time evolution in the assimilation provides a means to propagate error covariance consistent with time variant interactions between state quantities (Kalnay, 2003; Cohn, 1997) including the cloud state and atmospheric environment. This is especially relevant in cloud state estimation in which a mesoscale cloud state and its environment are rapidly changing.

In CIRA we developed a 4D variational (4DVAR) data assimilation algorithm with a mesoscale, cloud resolving weather prediction model to study assimilation of satellite radiance and other weather measurements in problems of high resolution weather analysis under all weather conditions, including clouds. The current choice of mesoscale weather prediction model is the Colorado State University Regional Atmospheric Modeling System (Cotton, et al, 2003). The new 4DVAR algorithm is designated Regional Atmospheric Modeling and Data Assimilation System (RAMDAS) . In this paper we present application of RAMDAS to the problem of continental stratocumulus cloud state analysis using GOES 9 imager visible and infrared measurements.

The content of this paper is as follows. The RAMDAS algorithm is briefly described in section 2. The observed continental stratus case and RAMS forecast are presented in section 3. Data assimilation experiments and results are discussed in sections 4. The summary and conclusions are presented in section 5.

2. 4D data assimilation algorithm

The RAMDAS algorithm has 4 major components: 1) Nonlinear forecast model, 2) observational operators, 3) adjoint of the forecast model and 4) minimization algorithm.

2.1 Forecast model

The RAMS is a well-known and tested non-hydrostatic, cloud-resolving research model (Cotton et al., 2003). Detail description of RAMS is available in Cotton et al. (2003) and the references therein. Of interest in this paper are the clouds, precipitation and vertical mixing parameterizations. The clouds and precipitation in RAMS are explicitly predicted via a microphysics parameterization that features a one-moment scheme (mixing ratio) for cloud liquid water (Walko et al. 1995) and a two-moment scheme (mixing ratio and number concentration) for six other hydrometeor types, including pristine ice, aggregates, snow, graupel, hail, and rain (Meyers et al. 1997). The hydrometeor size distribution is approximated by a Gamma distribution with a prescribed width. Although a more sophisticated bin microphysics parameterization is also available within RAMS (Feingold et al. 1996) this study utilized the bulk cloud microphysics scheme. The turbulence parameterization option used in this study is level 2.5 scheme by Mellor and Yamada (1974).

2.2 Adjoint model

The adjoint model in RAMDAS is an adjoint of the true tangent linear of RAMS. The linearization was performed with respect to full model solution at every time step. This means that the reference state for the adjoint integration is saved every time step in the forward forecast model integration. This feature requires large amounts of data storage but ensures highest accuracy of the adjoint solution (Errico et al, 1993). The adjoint in RAMDAS includes all physical parameterizations as in RAMS with the exception of the atmospheric radiation and convective parameterizations. The atmospheric radiation parameterization was assumed secondary for the short-term cloud forecast in the data assimilation. The convective parameterization was neglected because it is typically not used in high-resolution cloud prediction cases.

2.3 Observational operators

The version of RAMDAS used in the current study included only GOES imager radiance observations. The observational operator for these observations and its properties are described in detail in Greenwald et al. (2002, 2003). Only short summary of principal features is presented here. RAMDAS also includes an observational operator for conventional NWP observations. This observation operator, as well as the corresponding adjoint operator, was adopted from Weather and Research Forecast (WRF) model 3DVAR algorithm (Wu et al. 2001). The conventional NWP data were used in Zupanski et al. (2003).

The VISIROO is a system for forward computing of visible and infrared radiances in both clear and cloudy plane-parallel conditions and for adjoint computations of the sensitivity of these radiances to the input parameters from the forecast model. The forward part of the operator features two different radiative transfer (RT) models, both of which handle multiple scattering. The first computes radiances at solar wavelengths, called the Spherical Harmonic Discrete Ordinate Method

(SHDOM; Evans 1998), while the other computes infrared radiances using a delta-Eddington two-stream approach (e.g., Deeter and Evans 1998). The operator also makes use of anomalous diffraction theory (ADT) to estimate cloud single-scattering (i.e. optical) properties for all types of particles, including nonspherical ones. Extinction by gases is computed from the Optical Path TRANsmittance (OPTRAN) method (McMillin et al., 1995). The VISIROO has been verified against GOES imager data for a forecasted continental stratus system in Greenwald et al. (2002).

2.4 Minimization

The minimization algorithm in RAMDAS is the limited memory quasi-Newton algorithm of Nocedal (1980), with restart procedure of Shanno (1985) modified by Zupanski (1996). The empirical Hessian preconditioning is employed, reducing the satisfactory number of minimization iterations to about 10. The control vector is defined in terms of the potential temperature, Exner perturbation function, vertical wind, velocity potential, stream-function, total water mixing ratio, cloud hydrometeor mixing ratios and number concentrations. A set of forecast initial conditions and model errors for these physical quantities constitute the entire control variable space. Additional features of the minimization algorithm in RAMDAS are described in Zupanski et al. (2003).

3. **Case description and forecast**

This work continues that of previous analyses of a warm continental stratus simulation with RAMS (Greenwald et al., 2002) and the associated VIS and IR observation sensitivity study (Greenwald et al., 2003). Figure 1 shows GOES 9 visible images of this cloud system at 15 UTC (panel a) and 18 UTC (panel b) on 2 May 1996. In Greenwald et al. (2002, 2003) the continental stratus was simulated using a two-way nested grid configuration in RAMS with 5 km fine spacing inner grid, 25 km coarse spacing outer grid, 50 m vertical grid spacing in the boundary layer, and a total of 50 vertical layers up to 17 km. The vertical grid was the same for both horizontal grids. Only liquid phase of the bulk cloud microphysics parameterization in RAMS was used in the simulations, sufficient for the warm stratus. The analysis performed in Greenwald et al. (2002) for the inner grid shows that the forecast model is capable of highly realistic simulation of this cloud including distribution of cloud mass and its evolution over time.

A nested grid capability was not available in RAMDAS adjoint model neither was it possible to perform high resolution simulations in the outer, large domain due to computational limitations. These conditions required that the warm stratus forecast in the data assimilation experiments be performed over only a short period of 3 h and using the coarse grid resolution in the large domain. The coarse resolution simulation during 12-15 UTC placed the large stratus in the correct general area (framed sub-domain in Figure 2 to be compared to the equivalent in Figure 1a), but the cloud cover is over-predicted in central and north-east Texas and under-predicted in south Texas and in Oklahoma. The mean forecast error in brightness temperature of GOES 9 channel 4 (10.7μm) over the area with model stratus is, however, only -0.7 K, implying a skilled cloud forecast in the vertical. Standard deviation around this mean is 3.5 K.

The success of the low-resolution short-term simulation in the current study is not to be interpreted as suggesting that low-resolution grids for mesoscale cloud state estimation be utilized in general. It is unlikely that a horizontal grid spacing of 25 km could support successful simulations of bulk cloud microphysical processes in most cases. The current result simply shows that for the case under study the low horizontal resolution integration was sufficiently skillful for the purpose of initial testing of the cloudy radiance assimilation method in RAMDAS. Further studies on cloud state estimation with this system would include the appropriate high resolution grids after either the grid nesting capability is developed in the adjoint model or RAMDAS is ported to significantly more powerful computing platforms than were available for this study.

4. **Assimilation of GOES imager radiance measurements**

Greenwald et al. (2003) suggested that channels 1 and 2 (0.63 μm and 3.92 μm) of the GOES imager contain potentially the most information about warm stratus structure. These channels were used in the data assimilation experiments. First, we performed assimilation of each channel measurement assuming that only one pixel of data was available. The purpose was to estimate a 3D influence zone of the observation in one location. Then, the full set of observations was used over a rectangular area centered on the stratus (black rectangle in Figure 2).

In the one-pixel experiments, designated IR_1ob and VIS_1ob, for the infrared and visible channel, respectively, the cost function was reduced significantly after only few iterations. (Figure 3). Specifically, in the VIS_1ob experiment the cost function dropped to 20% of its original value after only first 2 iterations and then remained constant. In the IR_1ob experiment the cost function was reduced to 1% of the original value after only 3 iterations. This result is due to the efficient elimination of thin cloud in the assimilation after which the sensitivity of the cost function at the observation time to atmospheric variables in VIS frequency was reduced to exactly zero and to very small values in the IR experiment. The cost function gradient in temperature is reduced to zero in the VIS_1ob experiment after the cloud is removed in the second iteration because the sensitivity of water vapor absorption at 0.63 μm was assumed to be negligible. The water vapor absorption is considered for the 10.7 μm channel but the sensitivity to the temperature and water vapor resulting from that process is weak, as expected.

Overall, the one-pixel experiments show that the VIS and IR radiance assimilation is very effective locally in the presence of cloud and ineffective once it is removed from the forecast. This is not surprising, because these channels are known to be dominated by the surface radiation in the clear atmospheric columns. Adjustment of the surface condition was not considered in the current data assimilation experiments because the surface was assumed decoupled from the cloud evolution in short term. The dynamical response in the lower troposphere to the VIS and IR observations is of primary interest in this study because the atmospheric processes there can effectively influence the short term forecast.
The dynamical response of the modeled cloud environment confirm this hypothesis. The atmospheric columns around the observation point warmed and dried in the inversion layer above the cloud by increased mixing above the cloud top, thus causing the cloud removal locally.

The assimilation of IR radiance data over large rectangular area also show the same dynamical response mechanism. In this experiment (designated IR_cld), however, the warming and drying in some areas of the cloud is associated with cooling and moistening in other regions, depending on the forecast error sign relative to the observed cloudy radiances. The overall result from the IR_cld experiment is very good convergence of the 4DVAR algorithm (Figure 3) and significant reduction of the area mean brightness temperature.

5. Summary and conclusions

We present a method for explicit 3D cloud estimation from visible and infrared satellite radiance observations using 4DVAR data assimilation. This methodology is similar to variational data assimilation techniques already reported in other studies using cloud resolving models, however, the current technique utilizes high horizontal resolution satellite observations over an extended domain with strong sensitivity to cloud microphysics.

The following are main conclusions from the numerical experiments:

- Visible (0.63 μm wavelength) and IR (10.7 μm wavelength) observations significantly influence the model cloud forecast in the assimilation but only through the sensitivity to cloudy points in the model because the cost function of these observations is only weakly sensitive to atmospheric parameters.
- Negative cloud cover error (model – observed) was reduced only when a large number of observation points was used, causing dynamical correlations between the initial conditions and the observations through a combined influence of the nonlinear forecast and adjoint integration in the 4DVAR algorithm.
- The dominant mechanism responsible for correlating the observations and initial conditions for the case of warm stratus over the short term (3 h) was PBL vertical mixing . The warming and drying of the atmosphere within the cloud was associated with increased subsidence of warm air in the inversion layer while lifting from near the cloud base caused moistening, cooling and cloud enhancement near the cloud top. The lifting did not penetrate as deep as subsidence.
- The cloud forecast in the assimilation was improved in cloud cover and in IR brightness temperature compared to the GOES-9 measurements. The area average error in the brightness temperature at the end of assimilation was only –0.2 K.
- The 3 h cloud forecast in IR brightness temperature after assimilation was also improved where the cloud cover was correct but this forecast had significant cloud cover errors in one portion of the domain, similar to the control forecast. This regional cloud cover error appeared to be linked to the model error in the forecast near the lateral boundary and could not have been improved by the improved initial condition.

These results support our hypothesis that explicit prediction of cloud microphysics and an improved representation of clouds by satellite observations in a 4D data assimilation algorithm can render skilled mesoscale cloud state estimates. The results show that VIS and IR observations significantly influence the cloud forecast on mesoscales in the data assimilation but also strongly suggest the need to include other observations sensitive to local temperature and humidity to further constrain the solution. This is especially important in light of the fact that cloud forecast errors could be very large locally due to mismatch in cloud cover or cloud type between the model and satellite observations. To achieve the spatial and temporal resolution requirements of cloud state estimation, additional observations must be provided primarily by satellite remote sensing because most other observation sources are either too sparse (e.g., ground-based meteorological measurements) or limited in spatial extent (e.g., radar measurements). However, non-satellite observations should be used when and where available. The goal of atmospheric and cloud state estimation research is to determine a sufficient set of observations for a given problem. This can be achieved only by systematic study of the information content in experimentation with data assimilation techniques. RAMDAS was developed for this purpose and will continue to be tested and implemented with other satellite observations in the future in the cloud state estimation problem.

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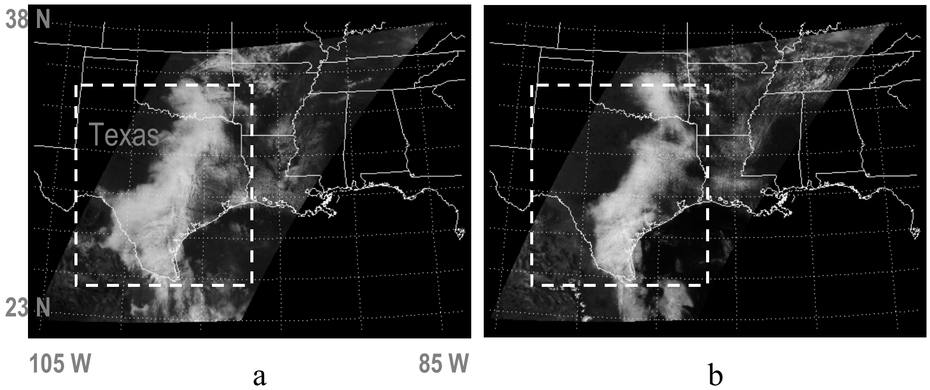

Figure 1. Observed visible image of warm stratus cloud system by the GOES 9 on May 2 1996 : a) 15 UTC and b) 18 UTC . The region outlined in white dashed frame indicates the domain within which the GOES observations of the warm stratus were used in the experiments.

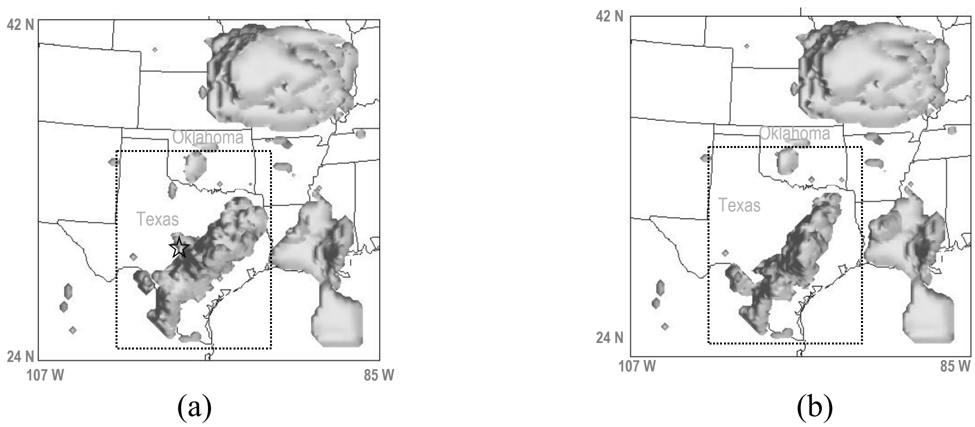

Figure 2. Model cloud forecast at 15, May 2 1996. Shown is top view of the 3D nonzero isosurface of cloud mixing ratio. The black dashed frame indicates the domain within which the GOES observations of the warm stratus were used in the experiments, as in Figure 1. a) before assimilation and b) after assimilation. The star in (a) indicates location of the observations used in IR_1ob and VIS_1ob experiments describes in section 4.1.

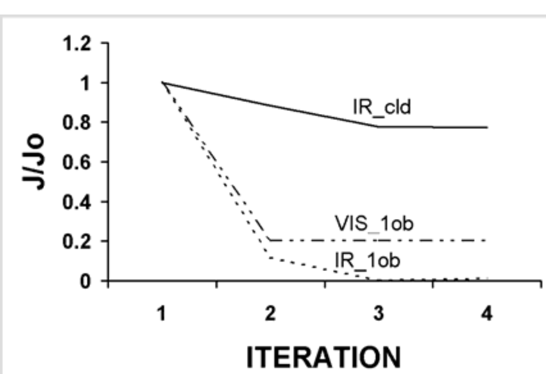

Figure 3. Normalized cost function as function of iteration for the three experiments described in section 4: VIS_1ob (dashed-dotted curve), IR_1ob (dotted curve) and IR_cld (full curve). The cost function is normalized by its starting value.